



When does less information translate into more giving to public goods?

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Abstract

This paper theoretically and experimentally investigates the impact of information provision on voluntary contributions to a linear public good with an uncertain marginal per-capita return (MPCR). Uninformed donors make contribution decisions based only on the expected MPCR (i.e. the prior distribution), while informed donors observe the realized MPCR before contributing. The theoretical analysis predicts that the impact of information on average contributions crucially depends on the generosity level of the population, modeled as a stochastic change in the pro-social preferences. In particular, a less generous population increases contributions substantially in response to good news of higher than expected MPCR and reduces contributions relatively little in response to bad news of lower than expected MPCR. The opposite is true for a more generous population. Thus, the theory predicts that information provision increases (reduces) average contributions when the population is less (more) generous. This prediction finds strong support in a two-stage lab experiment. The first stage measures subjects' generosity in the public good game using an online experiment. The resulting measure is used to create more and less generous groups in the public good lab experiment, which varies the information provided to these groups in the lab. The findings are in line with the theoretical predictions, suggesting that targeted information provision to less generous groups may be more beneficial for public good contributions than uniform information provision.

Keywords Information provision · Linear public good game · Other-regarding preferences · Lab experiment

JEL Classification H41 · C72 · C90

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1 Introduction

Private voluntary contributions have been increasingly viewed as a vital source of funding for public goods. For example, DonorsChoose, a fundraising platform for public school projects, has quickly gained popularity since its inception in 2000 and has raised close to \$640 million up-to-date.^{1,2} Other crowdfunding platforms that fundraise for public projects include Public Good,³ Razoo,⁴ and Pledge Music.⁵ Interestingly, while the non-profit sector is growing, with the number of non-profits surpassing 1.5 million, recent evidence suggests that individual donors are often poorly informed when making contributions. According to 2015 Camber Collective survey about private charitable giving in the U.S., “49% of donors don’t know how nonprofits use their money”.⁶ Such lack of information may have a significant impact on giving since existing lab experiments suggest that donors care about the use of their money, with more valuable projects receiving higher contributions (see Ledyard 1995; Cooper and Kagel 2016).

This paper uses a linear public good framework to theoretically and experimentally investigate the impact of more information about the marginal per-capita return (MPCR) of the public good on total contributions. In particular, it compares two information environments (treatments) corresponding to informed and uninformed donor populations (subject groups). An uninformed population (subject group) only observes the prior distribution of the MPCR and thus makes a contribution decision based on the expected MPCR. An informed population (subject group) observes the realized MPCR prior to contributing. By studying how donors respond to good news of higher than expected MPCR and bad news of lower than expected MPCR, we can determine whether information provision is on average beneficial or harmful for giving.

Interestingly, our theoretical analysis and experimental findings reveal that the relative response to good and bad news crucially depends on the generosity level of the population, which reflects the strength of donors’ pro-social motivations for giving. We find that a less generous population increases contributions substantially in response to good news and reduces contributions relatively little in response to bad news. The opposite is true for a more generous population that exhibits a stronger response to bad news than good news. As a result, we find that information provision is beneficial for giving in a less generous donor population, but harmful in a more generous donor population.

To glean more insight into this differential response to good and bad news, it is instructive to discuss how donors’ preferences impact the equilibrium contribution

¹ For more information, visit <https://www.donorschoose.org/about>.

² According to Charity Navigator, the overall contributions to education related causes in the US amounted to \$59.77 billion in 2016. For more information, see <https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=42>.

³ www.publicgood.com.

⁴ www.razoo.com.

⁵ <https://www.pledgemusic.com/>.

⁶ See <http://www.cambercollective.com/moneyforgood/>.

behavior in our theoretical model. We follow a growing literature that depicts agents as having other-regarding preferences (e.g. Rabin 1993; Fehr and Schmidt 1999; Bolton and Ockenfels 2000; Charness and Rabin 2002; Falk and Fischbacher 2006; Arifovic and Ledyard 2012). Such preferences are partially motivated by existing experimental findings revealing that, while it is payoff maximizing to contribute nothing to the public good and socially optimal to contribute the entire endowment, most contributions in the lab are in-between these two extremes (Ledyard 1995; Cooper and Kagel 2016). To capture this behavior, we follow Arifovic and Ledyard (2012) by modeling agents as having pro-social concerns, represented by agents' preference for higher average payoff in the population, and also having fairness concerns, represented by agents' dis-utility from obtaining lower than the average payoff. We refer to agents with stronger pro-social preferences as more generous since they have higher propensity to contribute.

The above preference specification gives rise to an equilibrium giving behavior by each agent that can be classified into one of three types based on their own generosity level: (1) selfish giving of 0 for low generosity; (2) generous giving of the entire endowment for high generosity; (3) conditional cooperative giving, matching the average expected contributions in the population, for moderate generosity. The individual generosity level is private information to each agent and thus the expected equilibrium giving takes into account the distribution of the pro-social preferences in the population. Quite intuitively, for a fixed MPCR, the expected equilibrium giving increases with the likelihood of generous giving and decreases with the likelihood of selfish giving.

Besides the distribution of the pro-social preferences, the equilibrium giving function is also affected by the MPCR. As the MPCR increases, the marginal cost of giving goes down while the social benefit goes up. This reduces the incentives for selfish giving in favor of cooperative and generous giving. As a result, the equilibrium giving function is increasing in the MPCR. Interestingly, the rate of increase is not constant, but instead it features increasing returns to MPCR when the MPCR is low (i.e. the expected giving function is convex in the MPCR for low values) and diminishing returns when the MPCR is high (i.e. the expected giving function is concave in the MPCR for high values). This is because at low MPCR, selfish giving dominates and an increase in the marginal return has a significant impact of incentivizing agents away from selfish to conditional and generous giving. This impact of increasing the MPCR eventually diminishes as the likelihood of selfish giving decreases substantially at high values of the MPCR.

The shape of the equilibrium giving function is instrumental in evaluating the impact of information provision. While a convex giving function tends to generate a greater response to good news and a weaker response to bad news, the opposite is true for a concave giving function. Interestingly, we find that a more generous population reaches diminishing returns faster, and thus exhibits a wider concave region. This is because more generous agents are more easily induced to give and contribute significant amounts even at lower values of the MPCR. As a result, a more generous population is less responsive to good news and more responsive to bad news. The opposite is true for a less generous population, which features increasing returns for a wider range of the MPCR and thus is more

responsive to good news than bad news. Consequently, the average informed giving is higher than the uninformed giving for a less generous population, while the opposite holds for a more generous population.

This novel finding of our model gives rise to testable hypotheses, which we experimentally investigate in the lab. Since our theoretical model suggests that the generosity level of the population plays a vital role in how agents respond to information, a defining feature of our experimental design is controlling for the generosity level of the sessions. We accomplish this by running our experiment in two stages. First, we conduct an online experiment to elicit subjects' generosity levels in the public good game prior to the lab experiment. Using this data, we create more and less generous groups in the lab, and inform the subjects about the generosity level of their session by using a neutral language. In the lab, subjects play a repeated one-shot linear public good game in groups of three with uncertain MPCR (either high (0.60) or low (0.40) with equal probability). There are two information treatments. In the Known MPCR treatment, subjects observe the randomly chosen MPCR before they make their contribution decisions. In the Unknown MPCR treatment, they are only informed about the distribution of the MPCR, and asked to make their contributions without observing which MPCR is chosen.

The experimental findings are in line with the theoretical predictions. In the more generous sessions, the average contributions in the Unknown MPCR treatment are not statistically different than the average contributions in the Known MPCR treatment under good news (MPCR of 0.60), but are statistically higher than the average contributions under bad news (MPCR of 0.40). Thus, on average, information reduces contributions to the public good in the relatively more generous sessions. The opposite is true for the less generous sessions: the average contributions in the Unknown MPCR treatment are not statistically different than the average contributions under bad news, but are statistically lower than the average contributions under good news. Thus, information is on average good for giving in the less generous sessions.

Our findings suggest that targeted information provision may be a successful strategy for increasing public good contributions. In particular, the model and the experimental results reveal that less generous donors are more responsive to good news about the returns from the public good. Thus, focusing on better informing these donors, who are often overlooked in fundraising campaigns, may be a more fruitful strategy than uniform information provision. In the next section, we briefly discuss how our findings contribute to the existing literature on public good provision.

2 Related literature

This paper connects two research strands that investigate two important factors that impact public good provision and cooperation: (1) information, and (2) the social preference composition of groups.

2.1 Information

Much of the earlier literature on public good provision assumes that donors operate under complete and perfect information (Ledyard 1995; Andreoni and Payne 2013; Vesterlund 2016). In reality, however, information is often limited, which has given rise to a more recent trend of studying public good provision under incomplete and imperfect information.

On the theoretical front, there is sparse literature that studies public good provision under incomplete information about the public good value. In particular, in the context of discrete public goods, Menezes et al. (2001), Laussel and Palfrey (2003), and Barbieri and Malueg (2008, 2010) introduce private information about donors' heterogeneous valuations of the public good, while Krasteva and Yildirim (2013) endogenize the choice of information acquisition and find that more information about one's own value improves giving. In contrast, our current setting features a public good with homogeneous returns and finds that more information about the return is not always beneficial.

Our paper is also related to the literature that studies the use of indirect signaling channels to transmit information to donors. In particular, Vesterlund (2003), Andreoni (2006), and Krasteva and Saboury (2019) study how the size and the form of a leadership gift by a large donor impacts other donors' beliefs about the quality of a public good.⁷ In a similar vein, Lange et al. (2017) study how a fundraiser may impact donors' beliefs by including a gift with the solicitation request. While these existing models are interested in the ability of different indirect channels to inform donors, our primary focus is on the direct impact of information provision on donors' willingness to contribute to public projects.

Our model and experimental set-up is cast as a continuous linear public good with an uncertain MPCR. In this respect, it is closest to the experimental literature that considers limited information about the returns. Although some of this literature focuses on information about others' valuation and/or endowment by incorporating heterogeneity in the public good environment (e.g. Marks and Croson 1999; Chan 1999), most of the focus has been on the impact of *uncertainty* about the MPCR. In particular, Gangadharan and Nemes (2009), Levati et al. (2009), Fischbacher et al. (2014), Stoddard (2015), Boulu-Reshef et al. (2017), Butera and List (2017) and Théroude and Zylbersztejn (2019) study how increasing the *riskiness* of the returns, in terms of a mean preserving spread, affects contributions. For example, Levati et al. (2009) compare the contributions to a linear public good with a certain return α to the contributions with an uncertain return that may take either high ($\alpha + a$) or low ($\alpha - a$) value with equal probability.⁸ Since both scenarios feature the same expected return α , the focus of the comparison is on the response to risk rather than the impact of good and bad news. In contrast, we are interested in how donors

⁷ In addition, Potters et al. (2005, 2007) experimentally investigate information revelation through leadership giving.

⁸ Although the findings are mixed, Levati and Morone (2013) and Stoddard (2017) show that the parameterization of the public good game can play an important role in determining the direction of this effect.

respond to good and bad news about the MPCR, which more closely represents the impact of information provision. To the best of our knowledge, our paper is the first to investigate public good contributions in this environment.

It is worth highlighting that our work is also related to a growing literature that studies the impact of variety of information (such as cost-to-donation ratio, recipients' or non-profits' characteristics, other donors' giving, and so on) on donations to non-profits and individual recipients outside the lab (e.g. Eckel et al. 2007; Shang and Croson 2009; Fong and Oberholzer-Gee 2011; Null 2011; Butera et al. 2017; Karlan and Wood 2017; Brown et al. 2017; Exley 2016, 2019; Portillo and Stinn 2018; Metzger and Günther 2019). These studies vary in the degree to which donors benefit from the non-profit's services, from donations to public radio (Shang and Croson 2009) to donations that benefit an anonymous third party (Fong and Oberholzer-Gee 2011). Pro-social considerations are likely a stronger determining motive for giving in the latter since donors are not direct beneficiaries.

Perhaps due to the significant variability in the nature of the provided information and the likely motives behind donors' contributions, the findings in the above studies are mixed. For instance, Fong and Oberholzer-Gee (2011) consider a dictator game setting with real-welfare recipients and find that information about the recipient is mostly used to withhold contributions from less preferred recipient types and thus information leads to an overall decline in aggregate transfers. Metzger and Günther (2019) focus on donations to NGOs that implement education projects for children and young adults in poor countries and find that the average donations increase in response to information about the recipient type and decrease in response to information about administrative costs. Butera et al. (2017) allow donors to choose from a large list of real charities with different missions and observe that response to program effectiveness depends on whether this information is provided privately or publicly. The benefit of our induced value public good experiment is that we are able to control both for the information that donors possess as well as the strength of the pro-social preferences in the population. Our findings suggest that the impact of information depends crucially on the pro-social preferences of donors, with information being less advantageous in the presence of more pro-social donors. This insight can be used in future field experiments to investigate how information provision about program effectiveness may differentially impact fundraising by non-profits that vary in the direct benefits they provide to their donors and the composition of their donor base.

2.2 Social preferences composition of groups

The second strand of related literature studies social preferences (i.e. other-regarding preferences) for giving. This literature has established that people have different motivations for giving and they can be classified into different types based on these motivations (see the following surveys: Camerer 2003; Fehr and Schmidt 2006; Cooper and Kagel 2016). While some people are selfish and do not give anything, others are conditional cooperators whose contributions depend on what others give (e.g. Brandts and Schram 2001; Fischbacher et al. 2001; Kurzban and Houser 2005).

Groups consist of individuals with different social preferences (i.e. types). The existing literature mainly focuses on how the group composition changes the level of cooperation and finds that the composition of social preference types in groups matters in achieving and maintaining high levels of cooperation (e.g. Burlando and Guala 2005; Gächter and Thöni 2005; Page et al. 2005; Gunthorsdottir et al. 2007; Gächter 2007; Ones and Putterman 2007; de Oliveira et al. 2015). One common finding in this literature is that contributions are higher in homogeneous groups with members who are more generous. Moreover, the existence of one selfish person in the group is enough to harm the groups' ability to cooperate (de Oliveira et al. 2015). We contribute to this research strand by studying the impact of information across two populations (subject groups) with different levels of generosity.

The rest of the paper is organized as follows: Sect. 3 introduces the theoretical model, and derives the testable hypotheses; Sect. 4 describes the experimental design that we use to test these hypotheses; Sect. 5 presents the results from the laboratory experiment; and Sect. 6 concludes.

3 Theory and hypotheses

The linear public good environment consists of groups of $N \geq 2$ agents. Each agent i is endowed with wealth W and chooses an amount g_i to allocate to a public good that benefits everyone in their group equally. The monetary payoff of agent i is

$$M_i = W - g_i + v \sum_{k=1}^N g_k$$

where $v \in (\frac{1}{N}, 1)$ denotes the marginal per-capita return (MPCR) of the public good. Clearly, the payoff maximizing strategy is $g_i = 0$ and the socially optimal strategy is $g_i = W$. Therefore, in the absence of other-regarding preferences, the unique Nash equilibrium is for all agents to contribute zero.

Since the above equilibrium behavior is a drastic departure from the existing experimental evidence (see Ledyard 1995), the literature has considered the possibility of other-regarding preferences, which feature a concern not only for one's own payoff, but also for others' payoffs both in absolute and relative terms (e.g. Rabin 1993; Fehr and Schmidt 1999; Bolton and Ockenfels 2000; Charness and Rabin 2002; Falk and Fischbacher 2006; Arifovic and Ledyard 2012). In particular, Arifovic and Ledyard (2012) stipulate the following utility function for agent i :

$$u_i(M_i, \bar{M}) = M_i + \beta_i \bar{M} - \gamma_i \max\{\bar{M} - M_i, 0\} \quad (1)$$

where $\bar{M} = \frac{1}{N} \sum_{k=1}^N M_k$ is the average earnings in the game. The agent-specific parameter β_i captures i 's pro-social motives for giving, which we refer to as the

individual i 's generosity level.⁹ Such motives are necessary to induce positive contributions. The parameter γ_i captures i 's inequality aversion, which generates disutility whenever i 's earnings fall below the average.

The utility representation in Eq. (1) is closely related to alternative utility specifications proposed by Fehr and Schmidt (1999) and Charness and Rabin (2002). In fact, Arifovic and Ledyard (2012) show that Eq. (1) is a linear transformation of these alternative specifications, apart from ignoring possible payoff effect from punishing non-cooperative behavior in a repeated setting.¹⁰ Our analysis focuses on Arifovic and Ledyard's specification since it yields a convenient representation of the agent's optimal contribution as a function of the average expected giving, \bar{g} . Such representation is both intuitive and provides a straightforward way of deriving the equilibrium expected giving $\bar{g}(v)$ as a function of the MPCR. To see this, note that Eq. (1) can be re-written as:

$$u_i(g_i, \bar{g}) = W - g_i + vN\bar{g} + \beta_i(W - \bar{g} + vN\bar{g}) - \gamma_i \max\{g_i - \bar{g}, 0\} \tag{2}$$

where $\bar{g} = \frac{1}{N} \sum_{k=1}^N g_k$. Maximizing (2) with respect of g_i gives rise to the following best response function:

$$g_i = \begin{cases} 0 & \text{if } \beta_i \leq \beta_1(v) \\ \bar{g} & \text{if } \beta_i \in [\beta_1(v), \beta_2(v, \gamma_i)] \\ W & \text{if } \beta_i \geq \beta_2(v, \gamma_i) \end{cases} \tag{3}$$

where

$$\beta_1(v) = \frac{N(1-v)}{Nv-1}, \quad \beta_2(v, \gamma_i) = \frac{N(1-v)}{Nv-1} + \gamma_i \frac{N-1}{Nv-1}.$$

Equation (3) reveals three types of contribution behavior: selfish giving of 0 for low β_i , unconditional generous giving of W for high β_i , and conditional cooperative giving of \bar{g} for intermediate β_i .¹¹ Given this best response function, the expected equilibrium giving must satisfy the following equation:

$$\bar{g}(v) = \Pr(\beta_i \geq \beta_2(v, \gamma_i))W + \Pr(\beta_i \in [\beta_1(v), \beta_2(v, \gamma_i)])\bar{g}(v). \tag{4}$$

Equation (4) states that the equilibrium expected giving is simply the weighted average giving of the generous agents, who give all their endowment, and the

⁹ In Arifovic and Ledyard's paper, this term is referred to as the level of altruism. Due to different definitions of altruism in the economics and psychology literature, we opt to avoid confusion by referring to β_i as the individual's generosity.

¹⁰ Refer to Section 2.2.2 in Arifovic and Ledyard (2012) for a detailed discussion about the relationship between these well-known utility specifications. In particular, the linear multiplier that converts the utility specification given by Fehr and Schmidt (1999) to Eq. (1) depends on the group size N , which is fixed in our analysis. Thus, these two specification should give rise to the same equilibrium behavior.

¹¹ Fischbacher et al. (2001) find evidence of these types of contribution behavior in the lab, with a third of subjects conforming to the Nash equilibrium prediction and another half behaving as conditional cooperators. Equation (3) reveals that this contribution behavior depends not only on the agent's individual characteristics captured by (β_i, γ_i) , but also on the MPCR.

conditional contributors, who match the expected average giving in the population. Re-arranging terms, we can re-write Eq. (4) as

$$\bar{g}(v) = \frac{1}{1 + \frac{\Pr(\beta \leq \beta_1(v))}{\Pr(\beta \geq \beta_2(v, \gamma_i))}} W \tag{5}$$

Thus, the expected equilibrium giving depends on the relative likelihood of the payoff maximizing (selfish) giving and socially optimal (generous) giving, i.e. $R(v) = \frac{\Pr(\beta \leq \beta_1(v))}{\Pr(\beta \geq \beta_2(v, \gamma_i))}$. As expected, the average giving is decreasing in the relative likelihood of selfish giving (i.e. $R(v)$) since it causes the conditional contributors to adopt more pessimistic beliefs about the average giving in the population.

To determine how the expected equilibrium giving varies with the MPCR, v , we need to take into account the distribution of other-regarding preferences since it affects the relative likelihood of selfish giving, $R(v)$. In particular, in order to focus attention on the comparative statics with respect to the population’s generosity level, we simplify the model by letting $\gamma_i = \gamma$ be identical across the population.¹² Furthermore, we model the pro-social preferences in the population as distributed according to an exponential distribution $\beta_i \sim \text{Exp}(1/\lambda)$ where higher λ represents a (stochastically) more generous population.¹³ This specification allows us to conduct comparative statics with respect to the generosity level of the population, captured succinctly by the parameter λ .

Given the expected equilibrium giving function and the distribution of pro-social preferences in the population, the following lemma describes how the expected giving varies with the MPCR, v , and the population’s generosity level λ .

Lemma 1 $\bar{g}(v)$ is increasing in $v \in \left(\frac{1}{N}, 1\right)$ with $\lim_{v \rightarrow \frac{1}{N}} \bar{g}(v) = 0$ and $\lim_{v \rightarrow 1} \bar{g}(v) = W$. Moreover, there exists a unique $\tilde{v}(\lambda) \in \left(\frac{1}{N}, 1\right]$ with the following properties:

- (1) $\bar{g}''(v) > 0$ for $v < \tilde{v}(\lambda)$ and $\bar{g}''(v) < 0$ for $v > \tilde{v}(\lambda)$;
- (2) $\tilde{v}(\lambda)$ is decreasing in λ with $\lim_{\lambda \rightarrow 0} \tilde{v}(\lambda) = 1$ and $\lim_{\lambda \rightarrow \infty} \tilde{v}(\lambda) = \frac{1}{N}$.

The formal proof of Lemma 1 is relegated to “Appendix 1”. Intuitively, it reveals that the equilibrium giving is increasing in the MPCR since higher v increases the net social benefit of giving, captured by $Nv - 1$, and decreases the individual cost of giving, captured by $1 - v$. Moreover, the equilibrium expected giving approaches zero as the net social benefit of giving becomes negligible (i.e. $v \rightarrow \frac{1}{N}$) and it approaches W as the marginal cost of giving becomes negligible (i.e. $v \rightarrow 1$).

¹² The results in this section readily generalize to a stochastic inequality aversion parameter γ_i as long as γ_i and β_i are independently distributed.

¹³ The use of a distribution function with infinite support ensures that the expected giving is always interior to the endowment and reaches the extreme values of 0 and W only in the limit when $v \rightarrow \frac{1}{N}$ and $v \rightarrow 1$, respectively. In addition, the exponential distribution provides a tractable way of varying the strength of the pro-social preferences of the population by changing the parameter λ . It is also worth noting that our analysis generalizes to other common distributions on \mathbb{R}^+ , which include the χ^2 and the Gamma distributions. The proof of this is available upon request.

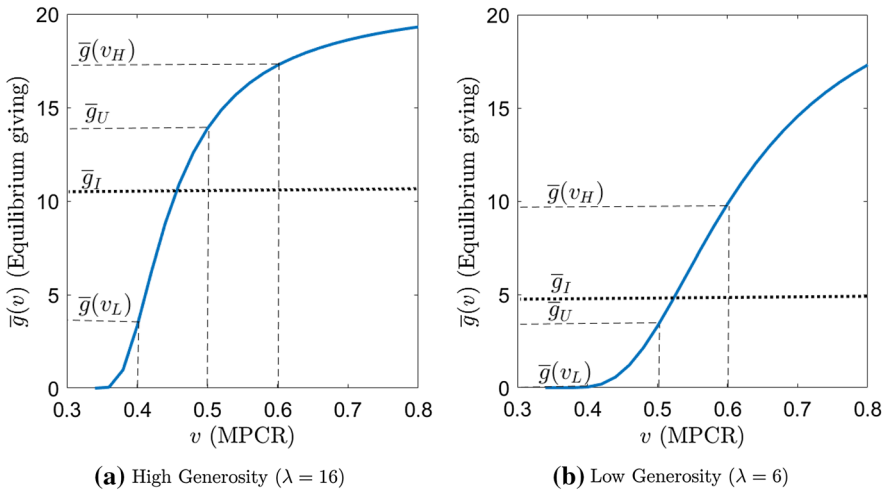


Fig. 1 Informed and uninformed giving for $\gamma = 4$, $v_L = 0.4$, $v_H = 0.6$, and $p_L = 0.5$

Interestingly, the first property reveals that the marginal benefit of increasing the MPCR is non-monotone and tends to diminish at higher values of the MPCR. In particular, the average giving $\bar{g}(v)$ exhibits increasing returns to MPCR for low values ($v < \tilde{v}(\lambda)$), but diminishing returns for high values ($v > \tilde{v}(\lambda)$). To grasp the intuition behind this dynamics, note that for low values (i.e. $v < \tilde{v}(\lambda)$), there is a significant number of agents who do not contribute. Thus, raising the MPCR in this case has an increasing marginal impact as it shifts a growing number of agents away from selfish to conditional and generous giving. However, this impact of increasing the MPCR eventually levels off as the number of selfish agents dwindles. Consequently, for high values of the MPCR ($v > \tilde{v}(\lambda)$), the marginal impact of further increasing the MPCR is diminishing as it induces a smaller number of agents to move away from selfish giving.

The second property further reveals that a more generous population, characterized by a larger λ , reaches diminishing returns to MPCR faster, i.e. $\tilde{v}(\lambda)$ is decreasing in λ . The reason is that for a more generous population, composed of individuals with relatively high β_i , inducing most agents to give requires only a modest increase in the MPCR. The opposite is true for a less generous population, in which significant portion of agents require a large increase in the MPCR in order to contribute.

Figure 1 illustrates a numerical example for two different values of λ (low and high generosity levels) and provides visual support for Lemma 1. It is evident from

Fig. 1 that $\bar{g}(v)$ is increasing in v for both generosity levels. While $\bar{g}(v)$ is convex at low values of v , it is concave at high values. Moreover, a more generous population (Fig. 1a) reaches diminishing returns of higher MPCR faster as illustrated by the fact that it is concave for a wider region of v (i.e. $\tilde{v}(16) < \tilde{v}(6)$).

The shape of the giving function described by Lemma 1 has an important implication for the impact of information provision. To see this, suppose that, as in the experimental design in Sect. 4, the MPCR (v) is drawn from a discrete distribution with $v = \{v_L, v_H\}$, where $\frac{1}{N} < v_L < v_H < 1$, and $\Pr(v = v_r) = p_r$ for $r = \{L, H\}$.¹⁴ In the absence of information, the agent's giving (\bar{g}_U) is based on the expected MPCR, $E[v]$. In contrast, an informed agent gives based on the realized MPCR, v , and thus the expected informed giving (\bar{g}_I) is the weighed average contributions under a high and a low MPCR.

$$\bar{g}_U = \bar{g}(E[v]); \quad \bar{g}_I = p_L \bar{g}(v_L) + p_H \bar{g}(v_H) \quad (6)$$

Clearly, information can either decrease giving by revealing low value v_L (bad news), or increase giving by revealing high value v_H (good news). The relative magnitude of the response to good and bad news depends of the shape of the giving function described by Lemma 1 and illustrated in Fig. 1. In particular, Fig. 1a illustrates the case of a generous population for which the giving function is mostly in the concave region. It is evident from the figure that the expected equilibrium giving responds more to bad news than good news, i.e. $|\bar{g}_U - \bar{g}(v_L)| > |\bar{g}_U - \bar{g}(v_H)|$. Consequently, when the population is rather generous, information is on average bad for giving, i.e. $\bar{g}_U > \bar{g}_I$. The opposite is true for a more selfish population that is likely to feature a convex giving function for a wider range of v . Thus, as Fig. 1b illustrates, the response to good news in this case is larger than the response to bad news (i.e. $|\bar{g}_U - \bar{g}(v_H)| > |\bar{g}_U - \bar{g}(v_L)|$), causing information to be on average beneficial for giving (i.e. $\bar{g}_I > \bar{g}_U$). The following proposition formalizes this dynamics.

Proposition 1 *There exist generosity levels $0 < \lambda_1 \leq \lambda_2 < \infty$ such that the expected informed giving exceeds the uninformed giving for $\lambda \leq \lambda_1$, while the uninformed giving exceeds the expected informed giving for $\lambda \geq \lambda_2$.*

The proof of Proposition 1 follows immediately from the Jensen's inequality and is relegated to "Appendix 1". The proposition states that while informed giving exceeds uninformed giving for a less generous population, information is detrimental for giving if the population is more generous. As discussed above, the key driver for this dynamics is that a less generous population is more responsive to good news than bad news, while the opposite is true for a more generous population.

Lemma 1 and Proposition 1 provide testable hypotheses that we investigate by using a lab experiment described in Sect. 4. In particular, our experimental design aims to test the following hypotheses.

¹⁴ To ease the exposition, we present the theoretical results using a two-point distribution for the MPCR since it corresponds to our experimental design in Sect. 4, but the theoretical results extend to any arbitrary non-degenerate distribution of the MPCR.

Hypothesis 1 In a less generous population, the agents' average response to good news is higher than their response to bad news. As a result, the informed giving, on average, is higher than the uninformed giving.

Hypothesis 2 In a more generous population, the agents' average response to good news is lower than their response to bad news. As a result, the informed giving, on average, is lower than the uninformed giving.

The above hypotheses imply that providing more information about the value of the public good should on average be beneficial for provision if the population is less generous, but detrimental for provision if the population is more generous. In the next section, we describe the experimental design used to test these two hypotheses in the lab.

4 Experimental design

In order to test our hypotheses, we need to control for the level of generosity in each session. We do so by conducting the experiment in two stages.¹⁵ In Stage 1, we measure the subjects' generosity level in the public good game by using an online experiment. One to two weeks later, using the information obtained from Stage 1, we invite some of them to the lab to participate in the second stage of the experiment.

Our experiment is a 2×2 between subjects design¹⁶: *Less Generous* versus *More Generous* and *Known MPCR* versus *Unknown MPCR*. Using the data collected in Stage 1, we create relatively more and less generous sessions in the lab. More specifically, we only invite subjects who were classified as relatively less generous to the *Less Generous* treatment; and we only invite subjects who were classified as relatively more generous to the *More Generous* treatment.

In Stage 2, subjects come to the lab to participate in a linear public good game described in Sect. 3. Subjects are placed in groups of three and play a one-shot linear public good game with an uncertain MPCR, which takes values of 0.4 or 0.6 with equal probability. They play the game for 10 rounds with random rematching. In the *Unknown MPCR* treatment, subjects make a contribution decision without knowing which MPCR will be used for that round. However, the subjects know that each realization of the MPCR is equally likely. In the *Known MPCR* treatment, subjects are informed about the realized MPCR for that round when they make their decisions. We pay subjects for one of the rounds picked at random at the end of the experiment. Finally, they fill out a survey. Below, we provide detailed information about each stage of the experimental design.

¹⁵ This aspect of our design is inspired by and similar to Burlando and Guala (2005), Gächter and Thöni (2005), and de Oliveira et al. (2015).

¹⁶ We run the *Known MPCR* and the *Unknown MPCR* treatments within subjects. Although subjects know that the experiment has two parts, they do not know anything about the second part when they play the first part. We only report the data from the first treatment played since the behavior in the first treatment contaminated the data from the second treatment (i.e. ordering effect).

Please indicate how many tokens (if any) you would like to contribute, for each possible average tokens contributed by other two group members:

	Your Contribution
if others' average contribution is 0 tokens	<input type="text"/>
if others' average contribution is 1 tokens	<input type="text"/>
if others' average contribution is 2 tokens	<input type="text"/>
⋮	
if others' average contribution is 20 tokens	<input type="text"/>

Fig. 2 Conditional contribution table

Stage 1: First, invitees receive an invitation email to participate in an incentivized online experiment with a possibility of being invited to an experiment in our lab. The online experiment, programmed in Qualtrics, consists of the Fischbacher et al. (2001) (henceforth FGF) conditional contribution game.¹⁷ In this game, each subject is endowed with 20 tokens (1 token = \$0.40), assigned to a group consisting of two other members, and asked to play a linear public good game with an MPCR of 0.50. Each subject makes two decisions: Decision 1 and Decision 2. In Decision 1, subjects state how many of their tokens, if any, they would like to contribute to a group project (unconditional contribution) that benefits everyone in their group equally. Next, in Decision 2, they fill out a conditional contribution table (see Fig. 2). In this table, they indicate how many tokens they would like to contribute to the group project *conditional* on the other group members' average contribution in Decision 1. For example, they state how much they would like to contribute if the other group members contributed 0 tokens on average in Decision 1, how much they would like to contribute if others contributed 1 token on average in Decision 1, and so on. Thus, in Decision 2, subjects make a total of 21 conditional contribution decisions.

After all subjects have participated in the online experiment, we randomly construct groups of three. Next, for each group, we randomly pick two group members for which Decision 1 will be implemented. We implement Decision 2 for the other group member. In other words, we randomly determine which of the two group members' unconditional contribution decisions will be implemented. Depending on the average unconditional contribution made by these two group members, we implement the other group member's conditional contribution as indicated in her conditional contribution table. Then, we calculate the earnings accordingly. The payments for the online experiment are delivered by Venmo, Paypal or cash. In order to avoid any potential contamination that may be created by the outcome of this stage, the subjects are not informed about the outcome and receive their payments for the online experiment only after Stage 2 is conducted.

The FGF conditional contribution game described above is a good way to measure the generosity level (β_i) of the subjects in the public good game. It is commonly used in the literature (with over 2,000 citations) to classify subjects into types in the

¹⁷ Please see our online supplementary material for instructions.

public good game: selfish (or free-riders who contribute zero), conditional cooperator (subjects whose contributions depend on the others' average contribution) and pro-social (or full cooperators who contribute everything).¹⁸ As described in Sect. 3, each subject's type is determined by their level of generosity, β_i . Those with a relatively low β_i are selfish, those with a high β_i are pro-social and others with a β_i somewhere in between are conditional cooperators. Since one of our goals is to create more and less generous groups in the lab, we calculate a measure for each subject by using the data collected from the conditional contribution game in Stage 1. More specifically, for each subject we calculate the following parameter that works as a proxy for the subject's level of generosity (i.e. β_i):

$$\hat{\beta}_i = \frac{\sum_{j=0}^{20} (g_j^i - j)}{\sum_{j=0}^{20} j}, \quad (7)$$

where g_j^i is subject i 's stated conditional contribution in Decision 2 for an average contribution by others, $j = 0, 1, \dots, 20$. If a subject is selfish, who always contributes zero independent of the others' giving, then her $\hat{\beta}_i$ is equal to -1 . If a subject is pro-social, who always contributes all of her endowment independent of the others' giving, her $\hat{\beta}_i$ is equal to $+1$. If a subject is a perfect conditional cooperator, who perfectly matches the others' average contributions, then her $\hat{\beta}_i$ is equal to 0 . Overall, a subject of higher generosity tends to contribute a larger amount for any average contribution level of the other group members, resulting in a higher $\hat{\beta}_i$.

Next, we rank all the subjects based on their $\hat{\beta}_i$ and divide them into two equally populated samples using the median. This gives us two samples, one below the median and one above the median. The first sample includes selfish subjects as well as (weak) conditional cooperators, thus it is relatively less generous. The second sample is relatively more generous since it includes pro-social subjects who contributed everything as well as (pro-social) conditional cooperators. More information on the distribution of types in our experiment is provided in Sect. 5. Next, we use these two samples to control for the generosity level in the public good game in the lab as explained below.

Stage 2: After dividing the subjects into two equally populated samples, we invite them to participate in the second stage in the Economic Research Lab at Texas A&M University.

Subjects play a one-shot linear public good game in groups of three for ten rounds in the lab. The groups in each round are constructed randomly (stranger matching design). In each round, subjects start out with 20 tokens (1 token = \$0.50) in their individual accounts and are asked to decide how many of these 20 tokens, if any, they would like to contribute to a group project (g_i). The monetary payoff function for this game is as follows:

¹⁸ Boosey et al. (2019) shows the validity of this procedure to explain behavior in public good games. Also see Thöni and Volk (2018) that review 17 replication studies of FGF and show that the FGF findings are stable.

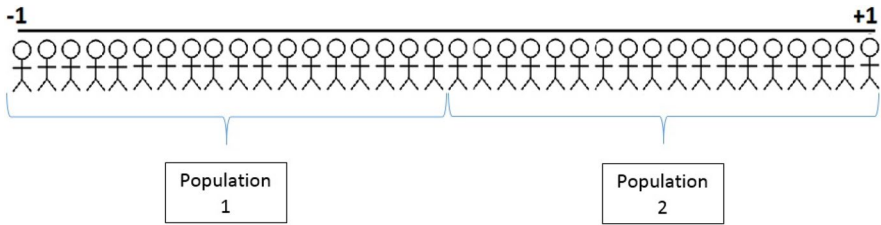


Fig. 3 Providing info about the session's generosity level

$$M_i = 20 - g_i + v \sum_{k=1}^3 g_k$$

The MPCR (v) of the public good is either 0.40 with 0.5 probability or 0.60 with 0.5 probability, which is determined randomly and independently for each group in each round.¹⁹ In the *Unknown MPCR* treatment, subjects make their contribution decision about the public good without knowing which MPCR is selected for that round, but they know that it is either 0.40 or 0.60 with equal probability. In the *Known MPCR* treatment, subjects are informed about the randomly chosen MPCR for that round and then are asked to make their contribution decisions about the public good. In both treatments, at the end of each round subjects receive feedback about their earnings, other group members' average contribution, and the randomly determined MPCR in the round.

In the *Less Generous (More Generous)* treatment, we only invite subjects whose $\hat{\beta}_i$ was below (above) the median. This is how we control for the level of generosity in each session. At the end of the instructions,²⁰ before the experiment starts, we remind subjects about their participation in the online experiment and provide them with information about the level of generosity in their session. Using a neutral language, we explain how a measure (i.e. $\hat{\beta}_i$) was created using their responses in the online experiment, how this measure should be interpreted (i.e. the higher the measure for a participant, the higher that participant's contributions), and how it was used to rank everyone as shown in Fig. 3. In the *Less Generous (More Generous)* treatment, we tell subjects that participants from Population 1 (2) were invited to that session.

¹⁹ The independent draw of the MPCR on the round and the group level eliminates any potential effect coming from the order of the MPCR.

²⁰ Please see our online supplementary material for instructions.

5 Results

Six experimental sessions were conducted in the Economic Research Lab at Texas A&M University in April 2017. Subjects were recruited through ORSEE (Greiner 2004), and the lab experiment was coded in z-Tree (Fischbacher 2007). The average earnings were \$9.85 in the first stage and \$21 in the second stage (including a show up fee of \$8 in the second stage).

A total of 360 subjects participated in the online experiment and 44 of these preferred not to be invited to the lab experiment. From the remaining group, we excluded 13 as their behavior in the online experiment seemed random. The final pool of subjects for Stage 2 was 303, and 111 of those also participated in the second stage.

5.1 Conditional contribution game findings

The attrition rate from Stage 1 to Stage 2 is high since when recruiting for the online experiment, it was impossible to predict whether a subject would be assigned to the *Less Generous* or the *More Generous* treatment sessions. This made it difficult to schedule session times that would be convenient for a large number of subjects. Nevertheless, it is important to confirm that there is no systematic difference in the generosity level of the subjects who participated in both stages versus the ones who participated in the first stage only. For this purpose, we look at Fig. 4 that presents the percentage distribution of $\hat{\beta}_i$, as computed using (7), for the 303 participants who were invited to Stage 2 in our experiment. The darker color represents the participants who participated in both stages (111 subjects), whereas the lighter color represents the participants who only participated in the first stage (192 subjects). Using the Kolmogorov–Smirnov equality of distributions test, we confirm that the difference

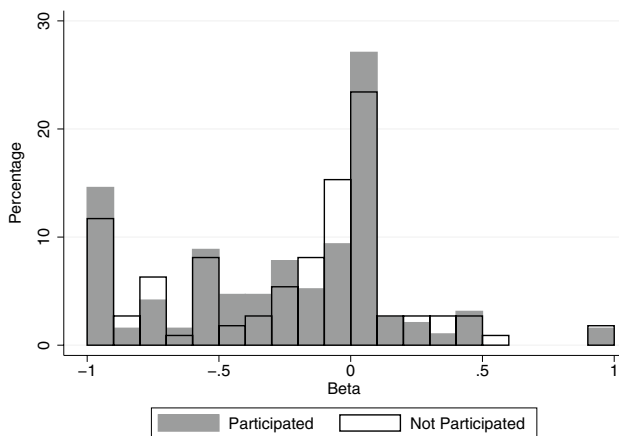


Fig. 4 Distribution of $\hat{\beta}_i$

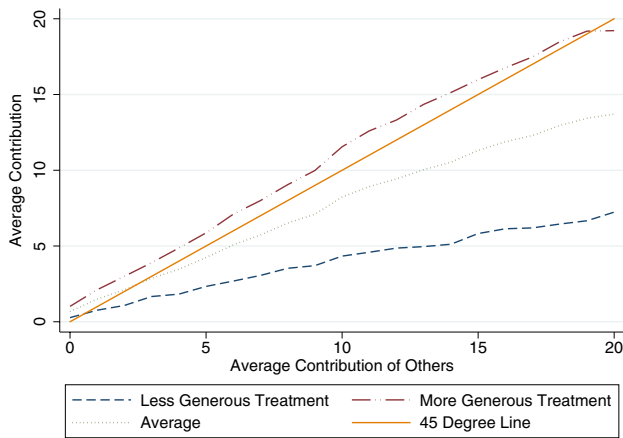


Fig. 5 Average contributions in stage 1 for each possible average contribution of others

between the distribution of $\hat{\beta}_i$ across these two samples is not statistically significant (p value is 0.536).

The mean and median of $\hat{\beta}_i$ from the online experiment are -0.25 and -0.11 respectively. The median is the cut-off point for the *More Generous* and the *Less Generous* sessions. The subjects whose $\hat{\beta}_i$ is below (above) the median are invited to the *Less Generous* (*More Generous*) treatment sessions. This is the only difference between these two treatments.

Figure 5 illustrates the conditional contribution decisions made in the online experiment (Stage 1) by those who also participated in the lab experiment (Stage 2). A perfect conditional cooperators, who always matches the others' average contribution, would be located on the 45 degree line. If a subject is located above this 45 degree line, it indicates that the subject contributed more than the average for all possible average contributions made by the other group members. In contrast, a subject who contributed less than the average would be located below this line. The average conditional contributions made for each possible contribution level of the others looks very similar to the FGF data. Figure 5 also illustrates the average conditional contributions made by the subjects in the *More Generous* and the *Less Generous* treatments separately. We provide a more detailed information regarding the behavior observed in the FGF game in “Appendix 2”.

5.2 The impact of information on public good contributions

In this sub-section, we present the results from Stage 2 of the experiment, where subjects played the public good game in the lab as described in Sect. 4.

Table 1 presents the average contributions made across treatments, which are computed by taking the average amount of tokens contributed across all ten periods by each subject. In the *Less Generous* treatment, we find that the *Unknown MPCR* contributions are not significantly different from the *Known MPCR* contributions

Table 1 Average contributions across treatments

	Unknown MPCR	Known MPCR	
		High MPCR	Low MPCR
Less generous	3.56 (n = 18)	6.67 (n = 33)	4.37 (n = 33)
More generous	12.41 (n = 24)	12.14 (n = 36)	9.24 (n = 35)

when the MPCR realization is low (unadjusted p value is 0.332, multiplicity adjusted p value is 0.332).²¹ However, the *Unknown MPCR* contributions are significantly lower than the *Known MPCR* contributions when the MPCR realization is high (unadjusted p value is 0.005, multiplicity adjusted p value is 0.009). Thus, subjects in the *Less Generous* treatment do not respond much to information when they receive bad news (MPCR of 0.40), but they substantially increase their contributions when they receive good news (MPCR of 0.60). This is in line with Hypothesis 1.

The above observation is also evident from Fig. 6 on the left, which shows the average contributions in all ten periods in the *Less Generous* treatment. It reveals that the uninformed contributions follow a similar path over time as the informed average contributions for the low MPCR. However, there is an upward jump in the informed average contributions for the high MPCR. The statement below summarizes this finding.

Result 1 In line with Hypothesis 1, in the *Less Generous* treatment, the average *Known—Low MPCR* contributions are not significantly different from the average *Unknown MPCR* contributions, while the average *Known—High MPCR* contributions are significantly higher than the average *Unknown MPCR* contributions.

In the *More Generous* treatment, we see the opposite trend. Table 1 reveals that the *Unknown MPCR* contributions are not statistically different from the *Known MPCR* contributions when the MPCR realization is high (unadjusted p value is 0.837, multiplicity adjusted p value is 0.837), but they are significantly higher than the *Known MPCR* contributions when the MPCR realization is low (unadjusted p value is 0.016, multiplicity adjusted p value is 0.027). Contrary to the *Less Generous* treatment findings, subjects in the *More Generous* treatment do not respond much to good news, but they significantly decrease their contributions upon obtaining bad news. This is also evident in Fig. 6 on the right, which shows the average contributions in all ten periods in the *More Generous* treatment. In the *More Generous* treatment, while the average uninformed contributions follow a similar path as the informed average contributions for the high MPCR, there is a decrease in average informed contributions for the low MPCR.

Result 2 In line with Hypothesis 2, in the *More Generous* treatment, the average *Known—Low MPCR* contributions are significantly lower than the average *Unknown MPCR* contributions, while the average *Known—High MPCR* contributions are not significantly different than the average *Unknown MPCR* contributions.

²¹ Following the multiple hypothesis testing method proposed by List et al. (2019), we report both the unadjusted p values (Remark 3.1) and the multiplicity adjusted p values (Theorem 3.1). The Mann–Whitney U test also yields very similar p values.

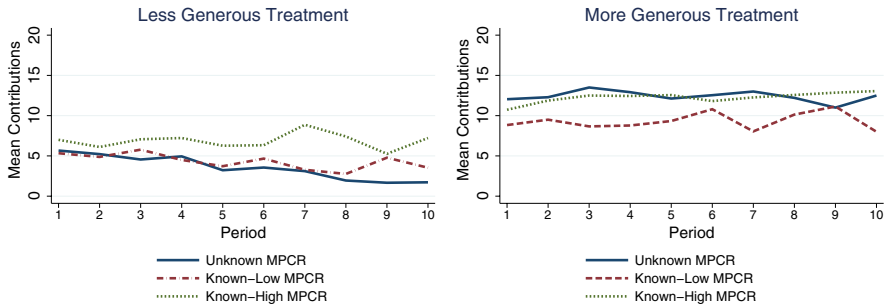


Fig. 6 Mean contributions

To check the robustness of our findings, we next present the regression results. Since the lowest possible contribution amount is zero tokens and the highest possible contribution amount is 20 tokens, we need to control for a potential censoring. Although a Tobit model is useful in accounting for censoring, it restricts the data by not allowing different motives behind the zero contribution.²² In other words, the Tobit model does not differentiate between the subjects who are selfish and would always contribute zero independent of the MPCR realization, and those who contribute zero due to the treatment (e.g. due to receiving bad news). Following Moffatt (2015, Ch 11.), we use a double hurdle model (also see Brown et al. 2017 for another example of using a hurdle model in experimental data).

The double hurdle model treats the probability of being a contributor and the extent of the contribution separately. Thus, by using this model, we can examine the impact of information on the extensive and the intensive margins. The results are reported in Table 2. We first run a Probit model regression using the cross section of all 111 subjects to analyze the factors that impact whether subjects contribute or not (i.e. being a potential contributor or not). The dependent variable in this probit model is *Contributed* which takes the value of one if the subject contributed a positive amount in any of the ten periods and zero otherwise.²³ The estimates of the first hurdle are presented in the first column of Table 2. There are a total of six subjects who contributed zero in all ten periods. Being in the *Known MPCR* treatment does not affect the *probability* of contributing to the public good. This implies that information does not impact contributions on the extensive margin. However, being in the *Less Generous* treatment significantly decreases the probability of contributing.

²² A similar reasoning can also apply to subjects who contribute everything. Since we have only one subject who contributed everything in all periods, we restrict our attention to only selfish types.

²³ As per the suggestion of an anonymous referee, we also run an alternative specification that takes into account the contribution behavior only in the last eight periods when determining whether a subject is a potential contributor. This aims to address a potential concern that, even with a stranger matching design, some selfish subjects could be contributing positive amounts early on in the game in order to induce giving by others (specifically by conditional cooperators) in later periods. The estimates from this specification are reported in Table A1 in the online supplementary materials and reveal that our findings are robust to this alternative specification.

Table 2 Double hurdle model regression results

	Probit (1)	Less generous treatment		More generous treatment	
		Tobit		Tobit	
		(2)	(3)	(4)	(5)
Less generous	- 0.836* (0.470)				
Known MPCR	0.004 (0.431)	2.332** (1.144)	0.865 (1.009)	- 2.559* (1.379)	- 4.675*** (1.179)
Known MPCR*high MPCR			3.211*** (0.773)		3.555*** (0.580)
Lagged others' average		0.258*** (0.074)	0.275*** (0.071)	0.149*** (0.046)	0.148*** (0.054)
Beta		- 0.976 (2.365)	- 0.816 (2.082)	9.695*** (2.367)	9.709*** (2.126)
Period		- 0.253** (0.111)	- 0.288*** (0.102)	- 0.0822 (0.118)	- 0.0203 (0.116)
Constant	2.126*** (0.458)	2.891* (1.704)	3.150* (1.612)	11.91*** (1.692)	11.51*** (1.393)
Observations	111	414	414	531	531

The robust standard errors clustered at the individual level are in parentheses. The dependent variable for the Probit model is Contributed which takes the value of 1 if the subject contributed at least once, and otherwise zero. The dependent variable for the panel data Tobit models is Contributions. The number of observations in column 1 is the total number of subjects participated in this study. The numbers of observations in the remaining four columns are the number of decisions made in 9 periods by subjects who contributed at least once across all 10 periods

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

This is not surprising given that we created the *Less Generous* vs. *More Generous* treatments based on the subjects' level of generosity measured in Stage 1.

Next, we run a Tobit model for the *Less Generous* and the *More Generous* treatments separately to study the factors that impact contributions *conditional* on contributing at least once (i.e. conditional on being a potential contributor). Thus, we exclude the subjects who failed the first hurdle. In columns (2)–(5), we report the marginal effects of the coefficients on the uncensored latent variable. The second and the third columns are created using the data collected in the *Less Generous* treatment and the last two columns are created using the data collected in the *More Generous* treatment. The dependent variable for all four columns is the contributions to the public good in each round.

The first model in columns 2 and 4 shows the average impact of information on contributions. The variable *Known MPCR* is a dummy variable for the *Known MPCR* treatment sessions. Thus, it takes the value of 1 if the subjects were informed about the realized MPCR for that round before they made their decisions. The model also controls for the following variables: *Lagged Others' Average*, which is the average contributions made by other group members in the previous round; *Beta*, which

is $\hat{\beta}_i$ that was computed using the data from the online experiment (i.e. Stage 1); and *Period*, which is simply the time trend. It is evident from columns 2 and 4 that in the *Less Generous* treatment, information about the MPCR has a positive and significant impact on contributions for those who are potential contributors. In contrast, in the *More Generous* treatment, information hurts the average contributions. These observations are summarized below.

Result 3 Consistent with Hypotheses 1 and 2, the overall impact of information about the MPCR is to increase average contributions to the public good in the *Less Generous* treatment and to decrease average contributions in the *More Generous* treatment.

The second model in columns 3 and 5 studies the impact of information separately for good and bad news. The variable *Known MPCR*High MPCR* is the interaction term between *Known MPCR* and *High MPCR*. The baseline in columns 3 and 5 is the *Unknown MPCR* treatment. Thus, the coefficient of *Known MPCR* shows the impact of receiving bad news. And, the coefficient of *Known MPCR*High MPCR* shows the impact of receiving good news relative to receiving bad news. Finally, the impact of receiving good news relative to the *Unknown MPCR* treatment is the summation of the coefficients of *Known MPCR* and *Known MPCR*High MPCR*.

Column 3 reveals that in the *Less Generous* treatment, when subjects find out that the MPCR is low, they do not significantly change their giving behavior relative to being uninformed. In other words, they do not respond to bad news. However, when they are informed and receive good news, they respond to information by significantly increasing their contributions. This provides further supporting evidence for Result 1. As suggested by Hypothesis 1, the relative response to good news is larger than bad news. Thus, overall, information is good for contributions.

In contrast, Column 5 reveals that in the *More Generous* treatment, when subjects find out that the MPCR is low, they significantly decrease their contributions relative to the uninformed contribution levels. When they receive good news of high MPCR, they respond by significantly increasing their contributions relative to receiving bad news. This provides further supporting evidence for Result 2. Furthermore, as suggested by Hypothesis 2, the negative response to bad news is stronger than the positive response to good news. Thus, on average, information hurts contributions significantly on the intensive margin.

Overall, Results 1–3 provide a strong support for the hypotheses emerging from our theoretical model. In particular, our regression analysis reveals that while information does not affect public good contribution on the extensive margin, it impacts contributions on the intensive margin and the sign of this impact depends on the generosity level of the sessions. In the *Less Generous* sessions, subjects contribute more on average when they are informed about the MPCR compared to when they are uninformed. As suggested by our theoretical analysis and supported by the experimental data, this is because their relative response to good news is greater than their response to bad news. Just the opposite is true for the *More Generous* sessions. In these sessions, subjects who are potential contributors give less on average to the public good when they are informed. This is due to their relative response to bad news being stronger than their response to good news.

6 Discussion and concluding remarks

The findings of this study have significant implications for fundraising. In particular, they suggest that targeted information provision may be a more fruitful strategy of increasing public good contributions than uniform information provision. While focusing information efforts on a less generous population may seem counter-intuitive at first, our findings suggests that such strategy may in fact increase average giving due to the differential impact of good and bad news on groups with different generosity level. A field experiment could provide a fruitful avenue for further investigation.

There is related research on “moral wiggle room” (Dana et al. 2007), which suggests that donors may strategically avoid information to justify selfish behavior. In a similar vein, donors have been found to use risk (Exley 2016; Cettolin et al. 2017), ambiguity (Haisley and Weber 2010; Garcia et al. 2019), beliefs about others (Tella et al. 2015), and performance metrics (Exley 2019) as an excuse not to give. Thus, it is worth discussing whether information avoidance could provide an alternative explanation for our findings. One difference between this body of research and ours is that these studies mostly use a dictator game environment, in which donors are not direct beneficiaries of the services provided by their contributions. In contrast, our public good framework allows for both personal benefits and pro-social concerns to affect contribution behavior. The most important difference, however, is that subjects in our study are either *exogenously* informed or uninformed, depending on the treatment. Thus, information avoidance as an excuse not to give is an unlikely explanation for our findings. Granted, it is plausible that subjects in the uninformed treatment could use the lack of information as an excuse not to give, despite knowing that each MPCR is equally likely. Although this could provide an alternative explanation for our findings in the less generous sessions, it fails to explain the behavior observed in the more generous sessions, and it is not clear why moral wiggle room may yield different results across treatments. Since it is beyond the scope of this paper, we leave it to future research.

Last but not least, our framework is limited by some factors that warrant further study both theoretically and experimentally. First, since donors themselves may be able to acquire information by conducting research about non-profits prior to contributing, an important direction for future research includes endogenizing the choice of information acquisition by donors. This would allow us to glean further insight about how information acquisition incentives differ across donors. Moreover, donors often have a choice among multiple non-profit organizations that serve related causes. Such competition among non-profits can impact both how donors respond to information about a particular non-profit as well as their willingness to acquire such information. Thus, a valuable extension of our framework is to consider multiple providers of a particular public good with possibly correlated valuations.

In addition, future research could investigate the impact of information when the returns from public good are *heterogeneous* rather than homogeneous since in many instances donors are not equal beneficiaries of the services/goods provided. While our framework features heterogeneity in donors' concern about their own benefit

versus the social benefit from the public good provision, allowing for exogenous heterogeneity in the returns would provide a richer environment to study how the type of information (i.e. private versus social returns) is most beneficial for public good provision. It is also often the case that ambiguity about the returns, rather than uncertainty, is impacting donors contributions. Thus, extending our framework to allow for ambiguity can provide further insights into the role of information provision in public good fundraising.

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Appendix 1

Proof of Lemma 1 For the purpose of this proof, note that

$$\frac{\partial \beta_1(v)}{\partial v} = -\frac{N(N-1)}{(Nv-1)^2} < 0 \tag{8}$$

and

$$\beta_2(v, \gamma) = (1 + \gamma)\beta_1(v) + \gamma, \tag{9}$$

implying that $\frac{\partial \beta_2(v, \gamma)}{\partial v} = (1 + \gamma)\frac{\partial \beta_1(v)}{\partial v}$.

To establish that $\bar{g}(v)$ is increasing in v , note by Eq. (5) that

$$\bar{g}'(v) = -\bar{g}(v)\frac{R'(v)}{1 + R(v)} \tag{10}$$

Moreover, since $\beta_i \sim \text{Exp}(1/\lambda)$, $R(v) = \frac{1 - e^{-\beta_1(v)/\lambda}}{e^{-\beta_2(v, \gamma)/\lambda}}$. Therefore, differentiating $R(v)$ with respect to v yields

$$\begin{aligned} R'(v) &= \frac{1}{\lambda} \frac{\partial \beta_2(v, \gamma)}{\partial v} e^{\beta_2(v, \gamma)/\lambda} - \frac{1}{\lambda} \left[\frac{\partial \beta_2(v, \gamma)}{\partial v} - \frac{\partial \beta_1(v)}{\partial v} \right] e^{(\beta_2(v, \gamma) - \beta_1(v))/\lambda} \\ &= -\frac{N(N-1)}{(Nv-1)^2} \frac{1}{\lambda} \left[e^{\beta_2(v, \gamma)/\lambda} + \gamma R(v) \right] < 0, \end{aligned} \tag{11}$$

where the last equality follows from Eqs. (8) and (9). Then, $R'(v) < 0$ and Eq. (10) immediately implies that $\bar{g}'(v) > 0$.

To show that $\lim_{v \rightarrow \frac{1}{N}} \bar{g}(v) = 0$, we need to show that $\lim_{v \rightarrow \frac{1}{N}} R(v) = \infty$. Note that $\lim_{v \rightarrow \frac{1}{N}} \beta_1(v) = \lim_{v \rightarrow \frac{1}{N}} \beta_2(v, \gamma) = \infty$. Therefore, $\lim_{v \rightarrow \frac{1}{N}} e^{-\beta_2(v, \gamma)/\lambda} = \lim_{v \rightarrow \frac{1}{N}} e^{-\beta_1(v)/\lambda} = 0$, resulting in $\lim_{v \rightarrow \frac{1}{N}} R(v) = \infty$. To see that $\lim_{v \rightarrow 1} \bar{g}(v) = W$ note that $\lim_{v \rightarrow 1} \beta_1(v) = 0$ and $\lim_{v \rightarrow 1} \beta_2(v, \gamma) = \gamma$. This implies that $\lim_{v \rightarrow 1} R(v) = 0$ and $\lim_{v \rightarrow 1} \bar{g}(v) = W$.

To establish the existence and uniqueness of $\bar{v}(\lambda)$ and its corresponding properties, we first derive $\bar{g}''(v)$ by differentiating $\bar{g}'(v)$ with respect to v , yielding

$$\bar{g}''(v) = \frac{\bar{g}(v)}{(1 + R(v))} \left[2 \frac{[R'(v)]^2}{1 + R(v)} - R''(v) \right]. \tag{12}$$

Differentiating Eq. (11) with respect to v and simplifying yields

$$R''(v) = \frac{N^2(N - 1)^2}{\lambda^2(Nv - 1)^4} \left[(e^{\beta_2(v, \gamma)/\lambda} + \gamma R(v)) \left(\frac{2\lambda(Nv - 1)}{(N - 1)} + \gamma \right) + (1 + \gamma)e^{\beta_2(v, \gamma)/\lambda} \right] > 0. \tag{13}$$

Substituting for $R'(v)$ and $R''(v)$ in Eq. (12) and simplifying results in

$$\begin{aligned} \bar{g}''(v) &= \frac{\bar{g}(v)}{(1 + R(v))} \frac{N^2(N - 1)^2}{\lambda^2(Nv - 1)^4} [e^{\beta_2(v, \gamma)/\lambda} + \gamma R(v)] \\ &\times \left[2 \frac{e^{\beta_2(v, \gamma)/\lambda} + \gamma R(v)}{1 + R(v)} - \frac{(1 + \gamma)e^{\beta_2(v, \gamma)/\lambda}}{e^{\beta_2(v, \gamma)/\lambda} + \gamma R(v)} - \frac{2\lambda(Nv - 1)}{(N - 1)} - \gamma \right]. \end{aligned}$$

Note that

$$\begin{aligned} g''(v) &\stackrel{\text{sign}}{=} \frac{1}{\lambda} \left[2 \frac{e^{\beta_2(v, \gamma)/\lambda} + \gamma R(v)}{1 + R(v)} - \frac{(1 + \gamma)e^{\beta_2(v, \gamma)/\lambda}}{e^{\beta_2(v, \gamma)/\lambda} + \gamma R(v)} - \frac{2\lambda(Nv - 1)}{(N - 1)} - \gamma \right] \\ &= \Omega(v, \lambda). \end{aligned} \tag{14}$$

Substituting for $R(v)$ in the above expression and further simplifying yields

$$\begin{aligned} \Omega(v, \lambda) &= \frac{1}{\lambda} \left[2 \frac{1 + \gamma(1 - e^{-\beta_1(v)/\lambda})}{e^{-\beta_2(v, \gamma)/\lambda} + 1 - e^{-\beta_1(v)/\lambda}} - \frac{1 + \gamma}{1 + \gamma(1 - e^{-\beta_1(v)/\lambda})} \right. \\ &\quad \left. - \frac{2\lambda(Nv - 1)}{(N - 1)} - \gamma \right]. \end{aligned} \tag{15}$$

Note that

$$\lim_{v \rightarrow \frac{1}{N}} \Omega(v, \lambda) = \frac{1 + \gamma}{\lambda} > 0, \tag{16}$$

since $\lim_{v \rightarrow \frac{1}{N}} \beta_1(v) = \lim_{v \rightarrow \frac{1}{N}} \beta_2(v, \gamma) = \infty$, and

$$\lim_{v \rightarrow 1} \Omega(v, \lambda) = \frac{1}{\lambda} [2e^{\gamma/\lambda} - 2\lambda - 2\gamma - 1] = \Omega^1(\lambda), \tag{17}$$

since $\lim_{v \rightarrow 1} \beta_1(v) = 0$ and $\lim_{v \rightarrow 1} \beta_2(v, \gamma) = \gamma$. Note that $\lim_{\lambda \rightarrow 0} \Omega^1(\lambda) = \infty$ and $\lim_{\lambda \rightarrow \infty} \Omega^1(\lambda) = -2$. Moreover, the term in brackets in Eq. (17) is strictly decreasing in λ , implying the existence a unique $\tilde{\lambda} > 0$ such that $\Omega^1(\tilde{\lambda}) = 0$. For $\lambda > \tilde{\lambda}$, $\Omega^1(\lambda) < 0$ and thus $\lim_{v \rightarrow 1} \Omega(v, \lambda) < 0$. Note that $\lim_{v \rightarrow \frac{1}{N}} \Omega(v, \lambda) > 0$ and $\lim_{v \rightarrow 1} \Omega(v, \lambda) < 0$ together imply the existence of $\tilde{v}(\lambda) \in (\frac{1}{N}, 1)$ that solves $\Omega(\tilde{v}(\lambda), \lambda) = 0$.

To establish the uniqueness of $\tilde{v}(\lambda)$, it suffices to show that $\frac{\partial \Omega(\tilde{v}(\lambda), \lambda)}{\partial v} < 0$. Note that by Eq. (12), $\Omega(\tilde{v}(\lambda), \lambda) = 0$ can be re-written as

$$\Phi(\tilde{v}(\lambda)) = 2[R'(\tilde{v})]^2 - R''(\tilde{v})(1 + R(\tilde{v})) = 0.$$

Thus, $\frac{\partial \Phi(\tilde{v}(\lambda))}{\partial v} < 0$ implies $\frac{\partial \Omega(\tilde{v}(\lambda), \lambda)}{\partial v} < 0$. Differentiating $\Phi(v)$ and evaluating at $\tilde{v}(\lambda)$ results in

$$\frac{\partial \Phi(\tilde{v}(\lambda))}{\partial v} = \frac{R'(\tilde{v})}{R''(\tilde{v})} [3[R''(\tilde{v})]^2 - 2R'''(\tilde{v})R'(\tilde{v})],$$

where we have taken into account that $1 + R(\tilde{v}) = \frac{2[R'(\tilde{v})]^2}{R''(\tilde{v})}$. By Eq. (11), $R'(\tilde{v}) < 0$ and by Eq. (13), $R''(\tilde{v}) > 0$. Therefore, $\frac{\partial \Phi(\tilde{v}(\lambda))}{\partial v} < 0$ requires $3[R''(\tilde{v})]^2 - 2R'''(\tilde{v})R'(\tilde{v}) = \zeta(\tilde{v}) > 0$. Somewhat tedious, but straightforward algebra yields:²⁴

$$\begin{aligned} \zeta(\tilde{v}) &= \frac{N^2(N-1)^2}{(N\tilde{v}-1)^4} \\ &\times \left[\frac{(1+\gamma)^2[R'(\tilde{v})]^2}{\lambda^2} - R'(\tilde{v})e^{\frac{\beta_2(\tilde{v})-\beta_1(\tilde{v})}{\lambda}} \frac{N(N-1)\gamma(4+2\gamma)}{\lambda^3(N\tilde{v}-1)^2} \right. \\ &\left. + \frac{3\gamma^2 N^2(N-1)^2}{(N\tilde{v}-1)^4 \lambda^4} e^{\frac{2(\beta_2(\tilde{v})-\beta_1(\tilde{v}))}{\lambda}} \right] \end{aligned}$$

Since $R'(v) < 0$, it follows immediately that $\zeta(\tilde{v}) > 0$ and thus $\frac{\partial \Phi(\tilde{v}(\lambda))}{\partial v} < 0$. This establishes the uniqueness of $\tilde{v}(\lambda)$. To establish property 1), note that by the continuity of $\Omega(v, \lambda)$ in v and Eq. (16), it follows that $\Omega(v, \lambda) > 0$ for all $v < \tilde{v}(\lambda)$, implying that $\bar{g}''(v) > 0$ for all $v < \tilde{v}(\lambda)$. The uniqueness of $\tilde{v}(\lambda)$ also implies that for all $\lambda > \tilde{\lambda}$ (i.e. $\Omega^1(\lambda) < 0$), $\Omega(v, \lambda) < 0$ for all $v > \tilde{v}(\lambda)$. This, in turn, implies that $\bar{g}''(v) < 0$ for all $v > \tilde{v}(\lambda)$.

To establish property (2), note first that the uniqueness of $\tilde{v}(\lambda)$ implies that for $\lambda < \tilde{\lambda}$, $\Omega(v, \lambda) > 0$ for any $v \in (\frac{1}{N}, 1)$. Therefore, for $\lambda < \tilde{\lambda}$, $\tilde{v}(\lambda) = 1$. For $\lambda > \tilde{\lambda}$, implicit differentiation of $\Omega(\tilde{v}(\lambda), \lambda) = 0$ results in

²⁴ To derive this expression, we have re-written Eq. (11) as $R'(v) = -\frac{N(N-1)}{(Nv-1)^2} \frac{1}{\lambda} \left[e^{\frac{\beta_2(v)-\beta_1(v)}{\lambda}} + (1+\gamma)R(v) \right]$. Using this expression, we have derived $R''(v)$ and $R'''(v)$, and used the resulting expressions to obtain $\zeta(\tilde{v})$.

$$\tilde{v}'(\lambda) = -\frac{\partial\Omega(\tilde{v}(\lambda), \lambda)/\partial\lambda}{\partial\Omega(\tilde{v}(\lambda), \lambda)/\partial v} \tag{18}$$

Recall that $\frac{\partial\Phi(\tilde{v}(\lambda))}{\partial v} < 0$, implies $\frac{\partial\Omega(\tilde{v}(\lambda), \lambda)}{\partial v} < 0$. Thus, it suffices to show that $\frac{\partial\Omega(\tilde{v}(\lambda), \lambda)}{\partial\lambda} < 0$. For this purpose, let $\tilde{\beta}_1(\tilde{v}, \lambda) = \frac{\beta_1(\tilde{v})}{\lambda}$, $\tilde{\beta}_2(\tilde{v}, \lambda, \gamma) = \frac{\beta_2(\tilde{v}, \gamma)}{\lambda}$, and $\omega(\tilde{\beta}_1, \tilde{\beta}_2) = 2\frac{1+\gamma(1-e^{-\tilde{\beta}_1})}{e^{-\tilde{\beta}_2}+1-e^{-\tilde{\beta}_1}} - \frac{1+\gamma}{1+\gamma(1-e^{-\tilde{\beta}_1})}$. Then, $\Omega(\tilde{v}, \lambda) = 0$ can be re-written as

$$\Omega(\tilde{v}, \lambda) = \frac{1}{\lambda} \left[\omega(\tilde{\beta}_1, \tilde{\beta}_2) - 2\lambda \frac{N\tilde{v} - 1}{N - 1} - \gamma \right] = 0. \tag{19}$$

Differentiating the above expression w.r.t. v yields

$$\begin{aligned} \frac{\partial\Omega(\tilde{v}, \lambda)}{\partial v} &= \frac{1}{\lambda^2} \left[\frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_1} \frac{\partial\beta_1(\tilde{v})}{\partial v} + \frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_2} \frac{\partial\beta_2(\tilde{v}, \gamma)}{\partial v} \right] - \frac{2N}{N - 1} \\ &= -\frac{1}{\lambda^2} \left[\frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_1} + \frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_2} (1 + \gamma) \right] \frac{N(N - 1)}{(N\tilde{v} - 1)^2} - \frac{2N}{N - 1} < 0 \end{aligned}$$

where we have substituted for $\frac{\partial\beta_1(\tilde{v})}{\partial v}$ and $\frac{\partial\beta_2(\tilde{v}, \gamma)}{\partial v}$ in the second equation using Eqs. (8) and (9). The strict inequality follows by our earlier result. Similarly, differentiating $\Omega(\tilde{v}, \lambda)$ w.r.t. λ results in

$$\begin{aligned} \frac{\partial\Omega(\tilde{v}, \lambda)}{\partial\lambda} &= \frac{1}{\lambda} \left\{ \left[-\frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_1} \frac{\beta_1(\tilde{v})}{\lambda^2} - \frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_2} \frac{\beta_2(\tilde{v}, \gamma)}{\lambda^2} \right] - 2\frac{N\tilde{v} - 1}{N - 1} \right\} \\ &= \frac{1}{\lambda} \left\{ -\left[\frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_1} + \frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_2} (1 + \gamma) \right] \frac{\beta_1(\tilde{v})}{\lambda^2} \right. \\ &\quad \left. - \frac{\gamma}{\lambda^2} \frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_2} - 2\frac{N\tilde{v} - 1}{N - 1} \right\} \\ &= \frac{1}{\lambda} \left\{ \frac{(N\tilde{v} - 1)(1 - \tilde{v})}{N - 1} \frac{d\Omega(\tilde{v}, \lambda)}{dv} - 2\frac{(N\tilde{v} - 1)^2}{(N - 1)^2} - \frac{\gamma}{\lambda^2} \frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_2} \right\} \end{aligned}$$

The first equality follows from $\Omega(\tilde{v}, \lambda) = 0$, the second equality follows from substituting for $\beta_2(\tilde{v}, \gamma)$ from Eq. (9) in the first one, and the last equality is derived by substituting for $\beta_1(\tilde{v})$ and re-arranging the terms. It is straightforward to verify that $\frac{\partial\omega(\tilde{\beta}_1, \tilde{\beta}_2)}{\partial\tilde{\beta}_2} > 0$ and thus $\frac{\partial\Omega(\tilde{v}, \lambda)}{\partial v} < 0$ implies that $\frac{\partial\Omega(\tilde{v}, \lambda)}{\partial\lambda} < 0$. Therefore, by Eq. (18), $\tilde{v}'(\lambda) < 0$ for $\lambda > \tilde{\lambda}$.

Finally, to establish that $\lim_{\lambda \rightarrow \infty} \tilde{v}(\lambda) = \frac{1}{N}$, note that Eq. (15) implies that $\lim_{\lambda \rightarrow \infty} \Omega(v, \lambda) = -2\frac{Nv-1}{N-1}$. By definition, $\Omega(\tilde{v}(\lambda), \lambda) = 0$ for $\lambda > \tilde{\lambda}$. Therefore,

$$\lim_{\lambda \rightarrow \infty} \Omega(\tilde{v}(\lambda), \lambda) = \lim_{\lambda \rightarrow \infty} -2\frac{N\tilde{v}(\lambda) - 1}{N - 1} = 0 \implies \lim_{\lambda \rightarrow \infty} \tilde{v}(\lambda) = \frac{1}{N}.$$

This completes the proof. □

Proof of Proposition 1 Given $\frac{1}{N} < v_L < v_H < 1$, by Lemma 1, there exist $\lambda_1 > 0$ such that $\tilde{v}(\lambda_1) = v_H$ and $\lambda_2 > \lambda_1$ such that $\tilde{v}(\lambda_2) = v_L$. Furthermore, by Lemma 1, $\bar{g}(v)$ is convex for all $v < v_H$ if $\lambda \leq \lambda_1$. Thus, by definition of convexity,

$$p_L \bar{g}(v_L) + p_H \bar{g}(v_H) > \bar{g}(p_L v_L + p_H v_H)$$

Analogously, for $\lambda \geq \lambda_2$, $\bar{g}(v)$ is concave for all $v \geq v_L$, implying the reverse inequality. \square

Appendix 2: Behavioral types in the conditional contribution game

A total of 360 subjects participated in the first stage of this experiment and played the Fischbacher et al. (2001) conditional contribution game. Using this data, we classify subjects' contribution behavior into the following categories:

- **Conditional Cooperators** About 73.6% of our subjects (265 subjects) are classified as the conditional cooperative types. Based on their contribution schedule, we further classify them into the following three distinct categories:

Pro-Social Conditional Cooperators 11.7% of our subjects (42 subjects) are classified as pro-social conditional cooperators. Their contributions are either equal to or more than the average contributions of others. On average, their contributions lie above the 45 degree line. The Spearman rank correlation coefficients of pro-social conditional cooperators are always positive and highly significant.

Perfect Conditional Cooperators 16.9% (61 subjects) are classified as perfect conditional cooperators. These subjects always perfectly match the contributions of others and thus their contributions on average lie exactly on the 45 degree line. Their Spearman rank correlation coefficients are equal to 1 and highly significant.

Weak Conditional Cooperators: 45% (162 subjects) are classified as weak conditional cooperators. The average contributions made by these subjects lie below the 45 degree line. While these subjects mostly exhibit weakly monotonic and increasing contribution behavior, 6.7% of our subjects (24 subjects) show some slight deviations from the increasing trend. The Spearman rank correlation coefficients of weak conditional cooperators are always positive and highly significant except for one subject whose coefficient is not significant.

- **Free Riders** 10% (36 subjects) are classified as free-riders or selfish. Independent of the others' average contributions, these subjects never contribute anything.
- **Hump-Shaped Contributors** About 6.7% (24 subjects) are classified as hump-shaped contributors. These subjects' contributions are increasing in others' average contributions but up to a level (about 10 tokens on average).

Beyond this level, their contributions start decreasing as others' average contributions increase.

- **Unconditional Full Cooperators** 1.7% of our subjects (6 subjects) are classified as unconditional full cooperators. They always contribute all of their endowment independent of others' average contribution.
- **Other** We classify the remaining 8% (29 subjects) as other. While, 3.9% (14 subjects) exhibits random behavior, about 3.6% (13 subjects) contributed a fixed amount such as 1 or 5 tokens with sometimes slight deviations. Interestingly, the contribution behavior for the 0.5% of subjects (2 subjects) exhibit a reserve hump-shape.

References

- Andreoni, J. (2006). Leadership giving in charitable fundraising. *Journal of Public Economic Theory*, 8(1), 1–22.
- Andreoni, J., & Payne, A. A. (2013). Charitable giving. *Handbook of Public economics*, 5, 1–50.
- Arifovic, J., & Ledyard, J. (2012). Individual evolutionary learning, other-regarding preferences, and the voluntary contributions mechanism. *Journal of Public Economics*, 96(9), 808–823.
- Barbieri, S., & Malueg, D. A. (2008). Private provision of a discrete public good: Efficient equilibria in the private-information contribution game. *Economic Theory*, 37(1), 51–80.
- Barbieri, S., & Malueg, D. A. (2010). Threshold uncertainty in the private-information subscription game. *Journal of Public Economics*, 94(11–12), 848–861.
- Bolton, G. E., & Ockenfels, A. (2000). ERC: A theory of equity, reciprocity and competition. *American Economic Review*, 90, 166–193.
- Boosey, L., Isaac, R. M., Norton, D., & Stinn, J. (2019). Cooperation, contributor types, and control questions. *Journal of Behavioral and Experimental Economics*. <https://doi.org/10.1016/j.soceec.2019.101489>.
- Boulu-Reshef, B., Brott, S., & Zylbersztejn, A. (2017). Does uncertainty deter provision to the public good? *Revue économique*, 68(5), 785–791.
- Brandts, J., & Schram, A. (2001). Cooperation and noise in public goods experiments: Applying the contribution function approach. *Journal of Public Economics*, 79(2), 399–427.
- Brown, A. L., Meer, J., & Williams, J. F. (2017). Social distance and quality ratings in charity choice. *Journal of Behavioral and Experimental Economics*, 66, 9–15.
- Burlando, R. M., & Guala, F. (2005). Heterogeneous agents in public goods experiments. *Experimental Economics*, 8(1), 35–54.
- Butera, L., & Horn, J. R. (2017). Good News, bad news, and social image: The market for charitable giving. George Mason University Interdisciplinary Center for Economic Science (ICES). SSRN <https://ssrn.com/abstract=2438230>.
- Butera, L., & List, J. A. (2017). An economic approach to alleviate the crises of confidence in science: With an application to the public goods game. No. w23335. National Bureau of Economic Research.
- Camerer, C. (2003). *Behavioral game theory: Experiments in strategic interaction*. Princeton: Princeton University Press.
- Cettolin, E., Riedl, A., & Tran, G. (2017). Giving in the face of risk. *Journal of Risk and Uncertainty*, 55(2–3), 95–118.
- Chan, K. S., et al. (1999). Heterogeneity and the voluntary provision of public goods. *Experimental Economics*, 2(1), 5–30.
- Charness, G., & Rabin, M. (2002). Understanding social preferences with simple tests. *Quarterly Journal of Economics*, 117, 817–69.
- Cooper, D. J., & Kagel, J. H. (2016). Other-regarding preferences. In J. H. Kagel & A. E. Roth (Eds.), *The handbook of experimental economics, volume 2: The handbook of experimental economics* (p. 217). Princeton: Princeton University Press.

- Dana, J., Weber, R. A., & Kuang, J. X. (2007). Exploiting moral wiggle room: Experiments demonstrating an illusory preference for fairness. *Economic Theory*, 33(1), 67–80.
- de Oliveira, A. C. M., Croson, R. T. A., & Eckel, C. (2015). One bad apple? Heterogeneity and information in public good provision. *Experimental Economics*, 18(1), 116–135.
- Eckel, C. C., De Oliveira, A., & Grossman, P. J. (2007). Is more information always better? An experimental study of charitable giving and Hurricane Katrina. *Southern Economic Journal*, 74(2), 388–411.
- Exley, C. L. (2019). Using charity performance metrics as an excuse not to give. *Management Science*. <https://doi.org/10.1287/mnsc.2018.3268>.
- Exley, C. L. (2016). Excusing selfishness in charitable giving: The role of risk. *The Review of Economic Studies*, 83(2), 587–628.
- Falk, A., & Fischbacher, U. (2006). A theory of reciprocity. *Games and Economic Behavior*, 54(2), 293–315.
- Fehr, E., & Schmidt, K. M. (1999). A theory of fairness, competition and cooperation. *Quarterly Journal of Economics*, 114, 817–68.
- Fehr, E., & Schmidt, K. M. (2006). The economics of fairness, reciprocity and altruism—experimental evidence and new theories. *Handbook of the Economics of Giving, Altruism and Reciprocity*, 1, 615–691.
- Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental economics*, 10(2), 171–178.
- Fischbacher, U., Gächter, S., & Fehr, E. (2001). Are people conditionally cooperative? Evidence from a public goods experiment. *Economics Letters*, 71(3), 397–404.
- Fischbacher, U., Schudy, S., & Teyssier, S. (2014). Heterogeneous reactions to heterogeneity in returns from public goods. *Social Choice and Welfare*, 43(1), 195–217.
- Fong, C. M., & Oberholzer-Gee, F. (2011). Truth in giving: Experimental evidence on the welfare effects of informed giving to the poor. *Journal of Public Economics*, 95(5), 436–444.
- Gächter, S. (2007). Conditional cooperation: Behavioral regularities from the lab and the field and their policy implications. In B. S. Frey & A. Stutzer (Eds.), *CESifo seminar series. Economics and psychology: A promising new cross-disciplinary field* (pp. 19–50). Cambridge, MA: MIT Press.
- Gächter, S., & Thöni, C. (2005). Social learning and voluntary cooperation among like-minded people. *Journal of the European Economic Association*, 3(2–3), 303–314.
- Gangadharan, L., & Nemes, V. (2009). Experimental analysis of risk and uncertainty in provisioning private and public goods. *Economic Inquiry*, 47(1), 146–164.
- Garcia, T., Massoni, S., & Villeval, M. C. (2019). *Ambiguity and excuse-driven behavior in charitable giving*. SSRN <https://ssrn.com/abstract=3283773>.
- Greiner, B. (2004). The online recruitment system ORSEE 2.0—a guide for the organization of experiments in economics. *Working Paper Series in Economics*, University of Cologne, 10(23), 63–104.
- Gunnthorsdottir, A., Houser, D., & McCabe, K. (2007). Disposition, history and contributions in public goods experiments. *Journal of Economic Behavior and Organization*, 62(2), 304–315.
- Haisley, E. C., & Weber, R. A. (2010). Self-serving interpretations of ambiguity in other-regarding behavior. *Games and Economic Behavior*, 68(2), 614–625.
- Karlan, D., & Wood, D. (2017). The effect of effectiveness: Donor response to aid effectiveness in a direct mail fundraising experiment. *Journal of Behavioral and Experimental Economics*, 66(C), 1–8.
- Krasteva, S., & Saboury, P. (2019). Informative fundraising: The signaling value of seed money and matching gifts. SSRN <https://ssrn.com/abstract=3390008>.
- Krasteva, S., & Yildirim, H. (2013). (Un) Informed charitable giving. *Journal of Public Economics*, 106, 14–26.
- Kurzban, R., & Houser, D. (2005). Experiments investigating cooperative types in humans: A complement to evolutionary theory and simulations. *Proceedings of the National Academy of Sciences of the United States of America*, 102(5), 1803–1807.
- Lange, A., Price, M. K., & Santore, R. (2017). Signaling quality through gifts: Implications for the charitable sector. *European Economic Review*, 96, 48–61.
- Laussel, D., & Palfrey, T. R. (2003). Efficient equilibria in the voluntary contributions mechanism with private information. *Journal of Public Economic Theory*, 5(3), 449–478.
- Ledyard, J. O. (1995). Public goods: A survey of experimental research. In J. H. Kagel & A. E. Roth (Eds.), *Handbook of Experimental Economics* (pp. 111–194). Princeton: Princeton University Press.
- Levati, M. V., & Morone, A. (2013). Voluntary contributions with risky and uncertain marginal returns: The importance of the parameter values. *Journal of Public Economic Theory*, 15(5), 736–744.
- Levati, M. V., Morone, A., & Fiore, A. (2009). Voluntary contributions with imperfect information: An experimental study. *Public Choice*, 138(1–2), 199–216.

- List, J. A., Shaikh, A. M., & Yang, X. (2019). Multiple hypothesis testing in experimental economics. *Experimental Economics*, 22, 773–793.
- Marks, M. B., & Croson, R. T. A. (1999). The effect of incomplete information in a threshold public goods experiment. *Public Choice*, 99(1–2), 103–118.
- Menezes, F. M., Monteiro, P. K., & Temimi, A. (2001). Private provision of discrete public goods with incomplete information. *Journal of Mathematical Economics*, 35(4), 493–514.
- Metzger, L., & Günther, I. (2019). Making an impact? The relevance of information on aid effectiveness for charitable giving: A laboratory experiment. *Journal of Development Economics*, 136, 18–33.
- Moffatt, P. G. (2015). *Experimetrics: Econometrics for experimental economics*. London: Palgrave Macmillan.
- Null, C. (2011). Warm glow, information, and inefficient charitable giving. *Journal of Public Economics*, 95(5), 455–465.
- Ones, U., & Putterman, L. (2007). The ecology of collective action: A public goods and sanctions experiment with controlled group formation. *Journal of Economic Behavior and Organization*, 62(4), 495–521.
- Page, T., Putterman, L., & Unel, B. (2005). Voluntary association in public goods experiments: Reciprocity, mimicry and efficiency. *The Economic Journal*, 115(506), 1032–1053.
- Portillo, J. E., & Stinn, J. (2018). Overhead Aversion: Do some types of overhead matter more than others? *Journal of Behavioral and Experimental Economics*, 72, 40–50.
- Potters, J., Sefton, M., & Vesterlund, L. (2005). After you—Endogenous sequencing in voluntary contribution games. *Journal of Public Economics*, 89(8), 1399–1419.
- Potters, J., Sefton, M., & Vesterlund, L. (2007). Leading-by-example and signaling in voluntary contribution games: An experimental study. *Economic Theory*, 33(1), 169–182.
- Rabin, M. (1993). Incorporating fairness into game theory and economics. *The American Economic Review*, 83, 1281–1302.
- Shang, J., & Croson, R. (2009). A field experiment in charitable contribution: The impact of social information on the voluntary provision of public goods. *The Economic Journal*, 119(540), 1422–1439.
- Stoddard, B. V. (2015). Probabilistic production of a public good. *Economics Bulletin*, 35(1), 37–52.
- Stoddard, B. (2017). Risk in payoff-equivalent appropriation and provision games. *Journal of Behavioral and Experimental Economics*, 69, 78–82.
- Tella, D., Rafael, R. P.-T., Babino, A., & Sigman, M. (2015). Conveniently upset: Avoiding altruism by distorting beliefs about others' altruism. *American Economic Review*, 105(11), 3416–42.
- Théroude, V., & Zylbersztejn, A. (2019). Cooperation in a risky world. *Journal of Public Economic Theory*. <https://doi.org/10.1111/jpet.12366>.
- Thöni, C., & Volk, S. (2018). Conditional cooperation: Review and refinement. *Economics Letters*, 171, 37–40.
- Vesterlund, L. (2003). The informational value of sequential fundraising. *Journal of Public Economics*, 87(3–4), 627–657.
- Vesterlund, L. (2016). Using experimental methods to understand why and how we give to charity. In J. H. Kagel & A. E. Roth (Eds.), *The handbook of experimental economics, volume 2: The handbook of experimental economics* (pp. 91–152). Princeton: Princeton University Press.

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